

A HYBRID GENETIC ALGORITHM FOR THE AIRLINE CREW ASSIGNMENT PROBLEM

Wagner P. Gomes and Nicolau D. F. Gualda

*Universidade de São Paulo, Escola Politécnica, Departamento de Engenharia de Transportes
Av. Professor Almeida Prado, Trav. 2, nº 83, Cidade Universitária, CEP 05508-900, São Paulo, SP, Brazil*

Keywords: Air transportation, Airline crew assignment, Metaheuristic, Hybrid genetic algorithm.

Abstract: A typical problem related to airline crew management consists of optimally assigning the required crew members to flights for a period of time, while complying with labor regulations, safety rules and policies of the airline. This problem, called the Crew Assignment Problem (CAP), is a combinatorial optimization problem. Hence, a Hybrid Genetic Algorithm (HGA) associated with a constructive heuristic and a local search was developed. The HGA was tested and applied to solve instances related to a Brazilian airline.

1 INTRODUCTION

The Crew Assignment Problem (CAP) treated in this study is defined as the problem of assigning a set of flights of a given aircraft type to a set of crew members of the same category (in this case, pilots).

CAP is a combinatorial optimization problem, making it difficult (or even impossible) to be solved by exact methods (Barnhart et al., 2003); (Kohn and Karisch, 2004); (Gopalakrishnan and Johnson, 2005).

Zeghal and Minoux (2006) formulated the CAP as a large scale integer linear problem. Since feasible integer solutions could not be reached for some instances, they proposed a heuristic based on a rounding strategy embedded in a partial tree-search.

Lucic and Teodorovic (2007) solved real instances through Simulated Annealing, Genetic Algorithm and Tabu Search. Souai and Teghem (2009) proposed a Genetic Algorithm associated with three local search heuristics to solve CAP.

In this study, a Hybrid Genetic Algorithm (HGA) is proposed, tested and applied to solve CAP instances related to a Brazilian airline. Relative to the research of Souai and Teghem (2009), the proposed HGA incorporates new mechanisms in the initial population generation, in the crossover operator and in the local search.

The paper is organized as follows. In Section 2, the proposed HGA is describes. Section 3 presents the results of tests and applications, and Section 4 the conclusions.

2 THE PROPOSED HGA

The input to a CAP is the set of flights to be covered. Initially, the flights are grouped to form duty periods that are series of sequential flights comprising a day's work for a crew member. Then, the duty periods are assigned to the crew members, considering the rules and regulations, the crew members' availabilities, and the minimization of crew total cost.

The rules and regulations applicable to CAP in the Brazilian context present some specific constraints, but comply with international ones (ANAC, 2011); (SNA, 2011).

Each crew member has a personalized calendar of availability, which takes into account a set of previously assigned activities. The crew members receive a fixed salary for 54 flying hours per month (minimum guarantee) and an additional remuneration for each exceeding flying hour. As a quality criterion, the total flying time should be balanced among the crew members, aiming at the equalization of salaries.

Figure 1 presents the HGA pseudocode. The HGA is executed until the number of generations (*Gen*) reaches a predefined value (*MaxGen*). At each generation, *N* new solutions (offspring) are produced, where *N* is the population size. The mutation operator is applied with probability *P_m* to one of the solutions generated at the crossover. A local search heuristic (LHS) is applied to the best solution produced at each generation. A new

population is formed by the best parents and offspring of the current generation.

```

function HGA (seed, MaxGen)
1. Build the initial population (Gen=0);
2. While (Gen < MaxGen) do
3.   Repeat
4.     Select parents for reproduction
       (roulette wheel method);
5.     Perform crossover;
6.     Perform mutation;
7.     Apply repair heuristic;
8.   Until (N offspring are created);
9.   Evaluate fitness of offspring;
10.  Apply local search heuristic;
11.  Select the new population (Gen++);
12. End While;
end HGA

```

Figure 1: The HGA pseudocode.

The following notation is considered:

- J : set of days of the planning horizon ($j \in J$);
- K : set of crew members ($k \in K$);
- F : set of flights to be covered in the considered planning horizon ($i \in F$);
- D : set of all legal duty periods ($d \in D$);
- $K_j \subseteq K$: set of crew members available to work on day $j \in J$;
- $F_j \subseteq F$: set of all flights that start on day $j \in J$;
- $D_j \subseteq D$: set of all legal duty periods that start on day $j \in J$;
- $D_j^* \subseteq D_j$: optimal (or initial) set of duty periods that covers all flights $i \in F_j$ exactly once;
- $D_j^k \subseteq D_j$: set of all legal duty periods that can be assigned to the crew member k on day j , satisfying all rules and regulations;
- F_{dj} : set of covered flights by duty period $d \in D_j$ on day $j \in J$;
- Fnc_{nj} : set of non covered flights by solution n on day $j \in J$;
- Foc_{nj} : set of over-covered flights by solution n on day $j \in J$;
- $Pena_{nj}$: penalty of the solution n related to non covered and over-covered flights on day $j \in J$, given by $Pena_{nj} = |Fnc_{nj}| + |Foc_{nj}|$;
- $Pena_n$: penalty of the solution n related to non covered and over-covered flights, given by $Pena_n = \sum_{j \in J} Pena_{nj}$.

2.1 Chromosome Encoding

A matrix $X = (x_{kj})_{|K| \times |J|}$ represents the chromosome.

A gene x_{kj} takes value 0 if the crew member k is not assigned to any duty period on day j (day free), value -1 if the crew member k is unavailable to work on day j , or a positive integer value d representing the code associated to the duty period $d \in D_j$ assigned to crew member k on day j .

The cost of a chromosome n is computed through expression (1), where c_k is the cost of the duty periods assigned to the crew member k , and y_k is equal to 1 if the crew member k is used in the solution n , and zero otherwise.

$$C_n = \sum_{k \in K} c_k y_k \quad (1)$$

The cost of the duty periods assigned to each crew member $k \in K$ is computed through expression (2), where α_1 is the fixed salary of a crew member, D_k is the set of duty periods assigned to the crew member k , ft_d is the total flying time of the duty period d , MG is the minimum guarantee of a crew member, α_2 is the additional remuneration for each exceeding flying hour, and c_d is the cost of duty period d .

$$c_k = \alpha_1 + \max \left\{ 0, \left(\sum_{d \in D_k} ft_d \right) - MG \right\} \times \alpha_2 + \sum_{d \in D_k} c_d \quad (2)$$

The cost of a duty period d is computed through expression (3) and equals the idle time cost of the crew member plus the overnight rest period cost. So, α is the work cost per minute of a crew member, $elapse$ is the maximum elapsed time allowed for a duty period, bt is the brief time, ft_d is the total flying time of the duty period d , dt is the debrief time, and oc_c is the overnight cost in city c .

$$c_d = \alpha \times [elapse - (bt + ft_d + dt)] + oc_c \quad (3)$$

2.2 Initial Population

The initial population of N chromosomes is built using a constructive heuristic. It is a simple greedy approach that sequentially defines the duty period assignments for the first day of the planning horizon, then for the second, and so on (day-by-day). This method is composed of the following steps:

- Step 1: Build the optimal (or initial) set of duty periods $d \in D_j^*$ that covers all flights $i \in F_j$ exactly once (duty period determination);

- Step 2: Build the set of crew members $k \in K_j$, and assign the duty periods $d \in D_j^*$ to the crew members $k \in K_j$ (duty period assignment).

Initially, a depth-first search procedure on a flight network is accomplished.

The flight network has a node for each flight $i \in F_j$ and arcs representing legal connections between flights. For each flight node, all legal duty periods that starts with this flight are enumerated.

Afterward, a model based on set partitioning problem is considered to determine the optimal set of duty periods $d \in D_j^*$ (expression (4)), where a_{id} is equal to 1 if flight i is covered by duty period d , and zero otherwise; and y_d is equal to 1 if duty period d is included in the set D_j^* , and zero otherwise.

$$D_j^* = \left\{ \min \sum_{d \in D_j} c_d y_d : \sum_{d \in D_j} a_{id} y_d = 1, \forall i \in F_j, y_d \in \{0,1\} \right\} \quad (4)$$

The set partitioning problem is NP-Hard (Nemhauser and Wolsey, 1999). So, it is very unlikely that there is an efficient algorithm which will always solve the problem optimally. Thus, a strategy based on savings heuristic is also proposed.

The savings heuristic is an adaptation of the parallel version of the savings heuristic introduced by Clarke and Wright (1964).

At first, each flight $i \in F_j$ represents a duty period and must be assigned to a distinct crew member. Next, iteratively, duty periods are merged based on savings $s_{ij} = d_{ic} + d_{cj} - d_{ij}$, where s_{ij} is the savings achieved by merging flights i and j in the same duty period, d_{ic} is the debrief time of flight i in city c , d_{cj} is the brief time of flight j in city c , and d_{ij} is the time interval between the flights i and j . Hence, the number of duty periods $d \in D_j^*$ needed to cover all flights $i \in F_j$ on day $j \in J$ is reduced.

The duty period assignment is addressed to produce a legal solution. The pseudocode of this step is show in Figure 2.

The choice order of the crew members (line 3) and duty periods (line 6) at each iteration influences the balance of total flying time among the crew members. Hence, eight combined alternatives were proposed for this choice, as shown in Table 1.

function Duty_Period_Assignment (D_j^*)

1. Build the set K_j ;
2. While ($|K_j| > 0$ and $|D_j^*| > 0$) do

3. Choose a crew member $k \in K_j$;
4. Build the set D_j^k ;
5. If ($|D_j^k| > 0$) then
6. Choose a duty period $d \in D_j^k$;
7. Assign the duty period d to crew member k ;
8. Update the set $D_j^k \leftarrow D_j^k \setminus \{d\}$;
9. End If
10. Update the set $K_j \leftarrow K_j \setminus \{k\}$;
11. End While;
12. Update the penalty Pen_{nj} ;

end Duty_Period_Assignment

Figure 2: Pseudocode for duty period assignment.

Three distinct strategies were considered, to say, DET, RAND and GRASP. In the DET strategy, the first crew member $k \in K_j$ is selected to receive a duty period d , or the first duty period $d \in D_j^k$ is selected for assignment to the crew member k .

In the RAND strategy, crew members or duty periods are randomly selected. The GRASP strategy follows a procedure based on the construction phase of the GRASP metaheuristic (Feo and Resende, 1995). In this case, a restricted candidate list (RCL) of the top q crew members $k \in K_j$ or p duty periods $d \in D_j^k$ is built, where $q = \lceil |K_j|/2 \rceil$ and $p = \lceil |D_j^k|/2 \rceil$. Finally, a crew member $k \in RCL$ or a duty period $d \in RCL$ is randomly chosen.

Table 1: Choice of crew members and duty periods.

Alternative	Combined strategy	Choice strategy of crew members	Choice strategy of duty periods
A	DET / RAND	DET	RAND
B	RAND / DET	RAND	DET
C	RAND / RAND	RAND	RAND
D	DET / GRASP	DET	GRASP
E	GRASP / DET	GRASP	DET
F	GRASP / GRASP	GRASP	GRASP
G	GRASP / RAND	GRASP	RAND
H	RAND / GRASP	RAND	GRASP

The crew members $k \in K_j$ are initially sorted in an ascending order of priority assignment, considering two groups: first, the crew members who have already received some duty period in the solution, and second, the crew members not used in the solution. Then, crew members of each group are reclassified in a total flying time ascending order.

The duty periods $d \in D_j^k$ are sorted in descending order of number of covered flights $i \in F_j$.

The constructive heuristic does not guarantee the coverage of all planned flights. In some cases the crew members can fly as passengers in a duty period. This type of flight is used to reposition a crew member to a city, or to enable the crew member to return to his home base. Consequently, the fitness of a chromosome n with non covered or over-covered flights is penalized (see Section 2.3).

2.3 Fitness Function

The fitness function of a chromosome is defined by expression (5), considered by Souai and Teghem (2009), where $FF_n \in [0,1]$ is the fitness function of the chromosome n , TC_n is the total cost of the chromosome n , and TC_{\max} is the largest total cost of the current population.

$$FF_n = (TC_{\max} - TC_n) / TC_{\max} \quad (5)$$

The expression (6), adapted from Souai and Teghem (2009), is used to calculate the total cost of each chromosome n of the current population, where $Pena_n$ is the penalty of the solution n related to non covered and over-covered flights, C_n is the cost of chromosome n (expression (1)), and σ_n is the standard deviation function of flying time assigned to the crew members in the chromosome n .

$$TC_n = \beta_1 \times Pena_n + \beta_2 \times C_n + \sigma_n \quad (6)$$

The parameters β_1 and β_2 must be adequately defined to hierarchically minimize the three terms of the expression (6).

The value of the parameter β_1 must ensure that $\beta_1 \times Pena_n \gg C_n, \forall n$. β_1 is calculated as follows: first, the inactive duty period cost is determined; then a illegal solution is generated, where the inactive duty period is assigned to the all crew members $k \in K$ in each day $j \in J$; and finally the value of β_1 is determined by expression (7), where $c_{\max} = \alpha_1 + c_d \times |J|$ is the maximum cost of illegal schedule assigned to a crew member k .

$$\beta_1 = c_{\max} \times |K| \quad (7)$$

The value of β_2 is defined through expression (8), where

$$A = \min_{n=1, \dots, N \text{ s.t. } C_n \neq 0} \{(\beta_1 \times Pena_n) / C_n\} \quad \text{and} \\ B = \max_{n=1, \dots, N \text{ s.t. } C_n \neq 0} \{\sigma_n / C_n\}.$$

$$\beta_2 = \begin{cases} (A + B) / 2 & \text{if } A \neq 0, \\ B & \text{if } A = 0. \end{cases} \quad (8)$$

2.4 Crossover and Mutation

The crossover operator consists of swapping g genes $x_{kj} \neq -1$ between the selected parents. At this point, three different crossover strategies were considered, named as SC (Simplified Crossover), PC (Probabilistic Crossover), and RC (Random Crossover). SC and PC strategies were introduced by Souai and Teghem (2009).

In the SC strategy, a number g is randomly defined, where $1 \leq g \leq \min\{|K|, |J|\}$. Next, g distinct genes are selected at random, so that two genes are not selected in the same row k or same column j . Finally, only the selected genes are swapped.

In the PC strategy, the random selection of g distinct genes is performed as in the SC strategy. Next, the selected genes that do not violate the legality of the solution are automatically swapped. For other selected genes, the exchange will depend on the degree of illegality of the solution, measured by the penalty of day j . More precisely, if $Pena_{X'j} \leq Pena_{Xj}$ then the exchange is accepted, where X is the current solution (parent) and X' is the new solution (offspring). Otherwise, the exchange is accepted with a probability $P = [Pena_{X'j} - Pena_{Xj} + 1]^{-1}$.

In the RC strategy, a number g is determined at random, where $1 \leq g \leq \max\{|K|, |J|\}$. Then, g distinct genes are randomly selected, so that two genes can be selected in the same row k or same column j .

The mutation operator consists to randomly swapping two genes $x_{kj} \neq -1$ of an offspring.

The legality of the solutions is not assured by the crossover and mutation operators. Therefore, the set D_j^k is built for each infeasible gene x'_{kj} . If $D_j^k \neq \emptyset$ then the set of flights F_{rh} to be subject to the repair heuristic is determined. If $F_{rh} \neq \emptyset$ then the duty period $d \in D_j^k$ that covers the largest number of flights $i \in F_{rh}$ and the least number of flights $i \notin F_{rh}$ is assigned to the crew member k on day j . Otherwise, if $F_{rh} = \emptyset$ then all flights $i \in F_j$ are covered and gene x'_{kj} is equal to zero. So, the duty period $d \in D_j^k$ that covers the least number of flights $i \in F_j$ is assigned to crew member k .

When a legal duty period is not identified in the repair heuristic ($D_j^k = \emptyset$), gene x_{ij} removed during crossover or mutation is restored. Accordingly, the legality of any solution at the end of the repair heuristic is ensured.

2.5 Local Search Heuristic (LSH)

A LSH is applied to the best offspring produced at each generation, in search for a better solution. Hence, given a solution x^* , two neighbouring solutions x' are explored through two distinct movements: the reassignment and the exchange movements.

The reassignment movement consists of removing a duty period assigned to a given crew member and then reassigning it to another crew member available on the same day. The exchange movement consists of swapping the duty periods assigned to two crew members on the same day. In both movements, the selection of days, crew members and duty periods is done at random.

If one of the neighbouring solutions x' is better than the solution x^* , then x^* is replaced by x' . The illegal solutions x' are discarded.

3 TESTS AND APPLICATIONS

The developed HGA was tested to solve two instances of the CAP associated to the operation of a Brazilian airline:

- Instance 1: assign 208 flights to 10 pilots for the period from 02/01/2011 to 02/14/2011;
- Instance 2: assign 416 flights to 12 pilots for the period from 02/01/2011 to 02/28/2011.

The HGA was implemented in C and compiled using the Microsoft Visual Studio 6.0. The program was run on a microcomputer PC Intel Core Duo, 1.66 GHz, with 1GB of RAM, under Microsoft Windows XP - SP3.

The mathematical model used in the duty period enumeration (Section 2.2) was solved by the linear programming package CPLEX 11.0 (ILOG, 2007). The random number generator was the Mersenne Twister (Matsumoto and Nishimura, 1964).

The HGA was run 10 times for each instance, with 10 different random seeds (seeds from 1 to 10 on the Mersenne Twister). For each run, it was considered a maximum of 50,000 generations, a population of 200 chromosomes, and a probability of mutation $Pm=0.3\%$.

It is important to emphasize that in the step 1 of the constructive heuristic both strategies achieved the same optimal set D_j^* . Accordingly, these strategies did not directly influence the HGA results.

Tables 2 and 3 summarize the HGA results for instances 1 and 2, respectively. The average total cost value was calculated by $TC_{avg} = \sum_{w=1}^{10} TC_w / 10$, where TC_w represents the best total cost value (expression (6)) obtained in run w .

Table 2: Results obtained by HGA for instance 1.

Initial population	Crossover strategy	Average total cost (TC_{avg})	Average CPU time (seconds)	% Deviation
A	SC	197.52	339	20.44%
	PC	194.26	256	18.45%
	RC	183.38	405	11.82%
B	SC	228.30	342	39.20%
	PC	216.58	267	32.06%
	RC	210.77	407	28.52%
C	SC	225.93	319	37.76%
	PC	220.72	264	34.59%
	RC	213.80	409	30.37%
D	SC	189.85	357	15.76%
	PC	179.09	264	9.20%
	RC	164.00	426	0.00%
E	SC	202.22	359	23.31%
	PC	184.97	262	12.79%
	RC	179.52	418	9.47%
F	SC	197.41	386	20.37%
	PC	196.82	260	20.01%
	RC	177.78	413	8.40%
G	SC	205.10	337	25.06%
	PC	201.20	263	22.68%
	RC	192.86	400	17.60%
H	SC	227.72	338	38.85%
	PC	219.86	279	34.06%
	RC	212.63	402	29.65%

Note that the D alternative with random crossover (RC) produced the best average total cost value for both instances. Alternatives D, E and F provided more robustness in the largest instance (instance 2). In contrast, alternatives A, C and G showed less robustness for the larger instances.

Predominantly, the RC crossover strategy led to more effective solutions than other crossover strategies (SC and PC) for both instances.

The average total cost value as a function of the association of HGA with the local search heuristic (LSH) was also evaluated, taking into account the results obtained for the D alternative combined with RC crossover strategy (the best one).

Without the association with LSH, HGA achieved an average total cost of 171.07 for instance 1 (4.31% higher) and an average total cost of 252.42 for instance 2 (2.49% higher).

Table 3: Results obtained by HGA for instance 2.

Initial pop.	Crossover strategy	Average total cost (TC_{avg})	Average CPU time (seconds)	% Deviation
A	SC	43,035.66*	455	17,374.58%
	PC	128,479.62*	387	52,068.99%
	RC	85,750.71*	795	34,718.97%
B	SC	393.67	501	59.85%
	PC	393.45	407	59.76%
	RC	382.21	826	55.19%
C	SC	43,109.16*	480	17,404.42%
	PC	391.80	407	59.09%
	RC	85,820.74*	821	34,747.41%
D	SC	271.29	570	10.16%
	PC	262.67	378	6.65%
	RC	246.28	807	0.00%
E	SC	290.57	491	17.99%
	PC	288.28	382	17.06%
	RC	279.24	813	13.38%
F	SC	279.20	485	13.37%
	PC	280.46	377	13.88%
	RC	259.47	803	5.36%
G	SC	85,755.44*	468	34,720.89%
	PC	85,762.53*	391	34,723.77%
	RC	43,040.22*	802	17,376.43%
H	SC	392.97	497	59.56%
	PC	393.88	405	59.93%
	RC	381.33	823	54.84%

*Solutions where flights were not all covered, resulting in penalty

4 CONCLUSIONS

This study treated the Crew Assignment Problem (CAP), important part of the airlines operational planning. A Hybrid Genetic Algorithm (HGA) associated with a constructive heuristic and a local search was developed. The HGA yielded feasible and efficient solutions for the considered instances with reduced CPU times (order of 8 to 14 minutes).

Elements of the GRASP metaheuristic combined with a constructive heuristic led HGA to be more robust and effective. The introduction of the local search heuristic (LSH) proved to be a way to get more effective solutions for the CAP. Besides, the RC (random crossover) strategy proposed in this study was more effective than other crossover strategies (SC and PC) found in the literature.

ACKNOWLEDGEMENTS

The authors acknowledge CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior), CNPq (Conselho Nacional de Desenvolvimento Científico), and LPT/EPUSP (Laboratório de Planejamento e Operação de Transportes da EPUSP) for supporting this research.

REFERENCES

- ANAC, 2011. *Lei do aeronauta (7.183/74)*. Available at: <<http://www2.anac.gov.br/biblioteca/leis/lei7183%20.pdf>> [Accessed 4 May 2011].
- Barnhart, C. et al., 2003. Airline crew scheduling. In: R. W. Hall, ed. *Handbook of Transportation Science*. Boston: Kluwer Scientific Publishers, p. 1-48.
- Clarke, G., Wright, J. W., 1964. Scheduling of vehicles from a central depot to a number of delivery points. *Operations Research*, 12, p. 568-581.
- Feo, T. A., Resende, M. G. C., 1995. Greedy randomized adaptive search procedures. *Journal of Global Optimization*, 6, p. 109-133.
- Gopalakrishnan, B., Johnson, E., 2005. Airline crew scheduling: State-of-the-art. *Annals of Operations Research*, 140 (2), p. 305-337.
- ILOG, 2007. *CPLEX 11.0 User's manual*. France: ILOG.
- Kohn, N., Karisch, S. E., 2004. Airline crew rostering: Problem types, modeling and optimization. *Annals of Operations Research*, 127, p. 223-257.
- Lucic, P., Teodorovic, D., 2007. Metaheuristics approach to the aircrew rostering problem. *Annals of Operations Research*, 155, p. 311-338.
- Matsumoto, M., Nishimura, T., 1998. Mersenne Twister: A 623-dimensionally equidistributed uniform pseudorandom number generator. *ACM Transactions on Modeling and Computer Simulation*, 8 (1), p. 3-30.
- Nemhauser, G. L., Wolsey, L. A., 1999. *Integer and combinatorial optimization*. Wiley – Interscience.
- SNA, 2011. *Convenção coletiva de trabalho - 2010/2012*. Available at: <http://www.aeronautas.org.br/images/stories/convcol/cc_2010_2012.pdf> [Accessed 4 May 2011].
- Souai, N., Teghem, J., 2009. Genetic algorithm based approach for the integrated airline crew-pairing and rostering problem. *European Journal of Operational Research*, 199, p. 674-683.
- Zeghal, F. M., Minoux, M., 2006. Modeling and solving a crew assignment problem in air transportation. *European Journal of Operational Research*, 175, p. 187-209.